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Do Online Courses Provide an Equal Educational Value Compared to In-Person Classroom Teaching? Evidence from U.S. Survey Data using Quantile Regression

Manini Ojha
O.P. Jindal Global University
India
&
Mohammad Arshad Rahman
Zayed University
UAE
Indian Institute of Technology Kanpur
India

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Abstract: Education has traditionally been classroom-oriented with a gradual growth of online courses in recent times. However, the outbreak of the COVID-19 pandemic has dramatically accelerated the shift to online classes. Associated with this learning format is the question: what do people think about the educational value of an online course compared to a course taken in-person in a classroom? We address this question and present a Bayesian quantile analysis of public opinion using a nationally representative survey data from the United States. We find that previous participation in online courses and full-time employment status favor the educational value of online courses. We also find that the older demographic and females have a greater propensity for online

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education. In contrast, highly educated individuals have a lower willingness towards online education vis-à-vis traditional classes. Regional variations in the propensity to value online classes also exist. Besides, covariate effects show heterogeneity across quantiles which cannot be captured using probit or logit models.
Keywords: Binary outcomes; COVID-19; online education; Gibbs sampling; public opinion; Pew Research Center

¿Los cursos en línea ofrecen el mismo valor educativo en comparación con la enseñanza presencial en el aula? Evidencia de datos de encuestas de EEUU mediante regresión cuantílica
Resumen: La educación ha estado tradicionalmente orientada al aula con un crecimiento gradual de los cursos en línea en los últimos tiempos. Sin embargo, el estallido de la pandemia de COVID-19 ha acelerado drásticamente el cambio a las clases en línea. Asociado con este formato de aprendizaje está la pregunta: ¿qué piensa la gente sobre el valor educativo de un curso en línea en comparación con un curso tomado en persona en un aula? Abordamos esta pregunta y presentamos un análisis cuantílico bayesiano de la opinión pública utilizando datos de una encuesta representativa a nivel nacional de los Estados Unidos. Encontramos que la participación previa en cursos en línea y la situación laboral a tiempo completo favorecen el valor educativo de los cursos en línea. También encontramos que los grupos demográficos mayores y las mujeres tienen una mayor propensión a la educación en línea. Por el contrario, las personas con un alto nivel educativo tienen una menor disposición hacia la educación en línea en comparación con las clases tradicionales. También existen variaciones regionales en la propensión a valorar las clases en línea. Además, los efectos de covariables muestran heterogeneidad entre cuantiles que no se pueden capturar mediante modelos probit o logit.
Palabras clave: Resultados binarios; COVID-19; educación en línea; Gibbs sampling; opinión pública; Pew Research Center

Os cursos online oferecem um valor educacional igual ao do ensino presencial em sala de aula? Evidência de dados de pesquisa dos EUA usando regressão de quantis
Resumo: A educação tem sido tradicionalmente orientada para a sala de aula, com um crescimento gradual dos cursos online nos últimos tempos. No entanto, a eclosão da pandemia COVID-19 acelerou dramaticamente a mudança para as aulas online. Associado a este formato de aprendizagem está a pergunta: o que as pessoas pensam sobre o valor educacional de um curso online em comparação com um curso presencial em sala de aula? Abordamos essa questão e apresentamos uma análise de quantis bayesianos da opinião pública usando dados de pesquisa nacionalmente representativos dos Estados Unidos. Descobrimos que a participação anterior em cursos online e o status de emprego em tempo integral favorecem o valor educacional dos cursos online. Também descobrimos que o grupo demográfico mais velho e as mulheres têm uma maior propensão para a educação online. Em contraste, indivíduos com alto nível de escolaridade têm menos disposição para a educação online em comparação com as aulas tradicionais. Também existem variações regionais na propensão de valorizar as aulas online. Além disso, os efeitos da covariável mostram heterogeneidade entre os quantis que não podem ser capturados usando modelos probit ou logit.

Palavras-chave: Resultados binários; COVID-19; Educação online; Gibbs sampling; opinião pública; Pew Research Center

Do Online Courses Provide an Equal Educational Value Compared to In-Person Classroom Teaching? Evidence from U.S. Survey Data using Quantile Regression

Advancements in technology have resulted in a proliferation of online educational opportunities over the last two decades. Allen & Seaman (2016) report that the growth rate of enrollments in online courses is expanding faster than the traditional classroom enrollments in the United States (US).[1] Even as academic leaders remain far more positive about traditional and blended pedagogical formats than fully online learning, the outbreak of the COVID-19 pandemic has compelled universities and educational institutes to adopt online education as an immediate substitute for in-person classrooms. This paradigm shift in education has drawn considerable attention from the media, and researchers across the globe. However, any research based on the acceptance of online education during this period of disturbance is likely to be a deviation from the natural relationship between education and technology. As institutions of higher learning integrate web-based tools into classroom instructions, we assert that it is important to assess the attitude towards digital education and its acceptance in a state of volition prior to the onset of the pandemic. This would also serve as a baseline for comparative studies which may be conducted during and post the pandemic in the future. With that in mind, in this paper, we analyze public opinion on the value of online education relative to traditional education using survey data from the Pew Social Trends and Demographics Project conducted by the Princeton Survey Research Associates International in 2011. To our knowledge, this is the only known national survey to collect data on public perceptions about online versus in-person classroom teaching.

Modelling public opinion on the value of online education presents a rich area for further study. In the early 2000s, despite significant skepticism from academics and pushback from the public, several universities invested in and adopted Massive Open Online Courses (MOOCs) as a teaching-learning format (Miller, 2014). Educational institutions today are compelled to rethink their pedagogical philosophies to incorporate either hybrid or fully-online teaching-learning formats, as a consequence of the ongoing pandemic. Students graduating in the current era have experienced some education using technology, either as a supplement to traditional classes, or as fully online courses. Correspondingly, faculty is expected to have the willingness and the ability to engage in pedagogy that utilises technology (Miller, 2014). While this trend towards instructional technology expands, there continue to be ambivalent perceptions about the quality of online education (Allen & Seaman, 2011; Chen et al., 2013; Otter et al., 2013). Therefore, we specifically address public opinion about the value of online education and the factors that influence it vis-à-vis traditional classes.

In particular, we analyze individual responses about the *educational value derived from online classes in comparison to in-person classroom* teaching using a nationally representative US survey data from the Pew Social Trends and Demographics Project. More specifically, we model the latent utility differential between online classes and traditional classes. This may be interpreted as a *propensity* or a *willingness* index, where higher propensity towards online education is characterized by large positive values and vice versa. Our investigation of educational perception is performed within the framework of the popular probit model and the state-of-the-art binary quantile regression. By

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[1] Roughly one in two individuals who have graduated in the last ten years have taken at least one online course in their degree program (Parker et al., 2011).

design, the probit model focuses on the average utility differential, but different individuals have varying degree of preference for online-learning relative to traditional classes. As such, to focus on the average is clearly inadequate. This limitation is overcome through the use of binary quantile regression which allows us to look at quantiles of the utility differential, thus giving a much richer and comprehensive view.

The results are compelling and ought to serve as a guide for future research. We find that an older demographic, individuals with full-time employment, individuals with previous online experience, and females display a propensity towards online education. Interestingly, our findings highlight that highly educated respondents have lower willingness for online education. We also note some amount of regional differences in the propensity to value online classes. All these covariates show considerable differences in covariate effects at different quantiles. Lastly, we find no convincing evidence of race or income having an effect on the propensity for online education.

Our results have some interesting implications from an educational policy perspective. First, with around two-thirds of the sampled population favoring in-person classrooms, online education is an unlikely permanent substitute for traditional classrooms. We find this to be especially prominent for highly educated students who are at the graduate and post-graduate levels. Therefore, notwithstanding the COVID-19 pandemic, universities ought to be cautious while making large investments in fully online degree programs for such students. Second, institutions of higher education could perhaps design online programs that cater to the specific needs of females, mid-career professionals and older individuals. With online courses offering greater flexibility in schedules by design, these groups of individuals are more likely to take advantage of them.

The remainder of the paper is organized as follows. In the following section, we provide a brief literature review of online versus in-person classroom teaching. Then, we outline the data used for our analysis including a descriptive summary. Next, we describe the quantile regression for binary outcome model and present a Markov Chain Monte Carlo (MCMC) algorithm for estimating the same. Thereafter, we present the findings of our study and discuss them in relation to the existing works in the literature. Finally, we conclude with a brief discussion on the implications of our study to educational research and policy. We end this section with three crucial questions which can provide fodder for future research.

Literature Review

Our paper makes two specific contributions to the existing literature on online education. Over the last few years, a sizeable body of literature on the demand and efficacy of online education, its scope to lower educational costs, student and faculty perceptions, and its impact on student learning outcomes have emerged (Allen & Seaman, 2011; Alpert et al., 2016; Bettinger et al., 2017; Cassens, 2010; Chen et al., 2013; Fendler et al., 2011; Figlio et al., 2013; Goodman et al., 2019; Hart et al., 2018; Joyce & Crockett, 2015; Kirtman, 2009; Krieg & Henson, 2016; Otter et al., 2013; Xu & Jaggars, 2013). However, much of the existing research focuses on one or two specific courses, or are limited within a selective college or university. For instance, Goodman et al. (2019) compare an online and in-person degree in Master of Science in Computer Science offered at Georgia Tech and document a large demand for the online program with nearly no overlap in the applicant pools. Analyzing survey data from a community college in California, Cassens (2010) finds no significant differences in students' performances in online and traditional teaching methods. Contrary to this, using data from one large for-profit university, Bettinger et al. (2017) find negative effects of online courses on student academic success and progression relative to in-person courses. On similar lines, Otter et al. (2013) find significant differences upon comparison of faculty and student perceptions of online courses versus traditional courses at a large public university in the south-eastern United States. As such, mixed evidence found owing to the narrow focus of these papers often brings their external validity into question. To this end, we attempt to address public opinion on educational value of online classes by utilising a nationally representative US survey data, thereby drawing conclusions for a population at large. This is the first contribution of our paper. Besides, some scholars such as Monroe (1998) and Paletz et al. (2013) argue that public policies should be guided by public opinion so that mass opinion and democracy is upheld, while Shapiro (2011) cites a large number of studies to argue that public opinion influences government policy making in the US. Consequently, a study of public opinion on mode of educational preferences may aid both researchers and educationists involved in policy making.

Furthermore, ambiguous views about the acceptance of online education make it imperative to investigate overall public opinion on the matter. There is evidence that the proportion of faculty who believe in the legitimacy of online education is relatively low. In addition, the proportion of faculty who perceive online education as more time intensive and requiring greater effort has seen a steady growth (Allen & Seaman, 2011). Contrary to this, students perceive such courses to be largely self-taught with minimal effort from the faculty (Chen et al., 2013; Otter et al., 2013). That being the case, our paper also contributes to a second body of literature that points towards the differential adoption and acceptance of technology in higher education across different demographics (Chen & Fu, 2009; Cooper, 2006; Cotten & Jelenewicz, 2006; Crain & Ragan, 2017; Jones et al., 2009; Norum & Weagley, 2006; Odell et al., 2000). Some papers document that the perceptions about an online learning environment is affected by employment status (Deming et al., 2015; Kizilcec et al., 2019; Simmons, 2014), previous online experience (Astani et al., 2010; Goode, 2010; Williams, 2006), and income levels (Horrigan & Rainie, 2006; Rauh, 2011). However, since online education is a matter of individual selection, individual characteristics may vary drastically across the utility derived from it. Traditional mean regression of the effects of covariates on the preference about online classes may mask important heterogeneity in individual choices. Our study is the first, of which we are aware, to offer new insights regarding the opinion on the educational value of online courses across the quantiles and latent utility scale. These differential effects across the latent utility scale may be of direct interest to policy makers and educationists as our methodology provides a more comprehensive picture.

Data

The study utilizes a nationally representative US survey data from the Pew Social Trends and Demographics Project, conducted over telephone between March 15–29, 2011, by the Princeton Survey Research Associates International. The survey was primarily for higher education and housing and contains information on 2,142 adults living in the continental US. The dependent variable in our study is the response to the question: *In general, do you think a course taken only online provides an equal educational value compared with a course taken in person in a classroom, or not?*. Responses are recorded either as *Yes*, *No*, or *Don't know/Refused*. The survey also consists of information on an array of other variables, some of which we utilize as covariates (independent variable) in our analysis. Upon removing the *Don't know/Refused* category and missing observations from our variables of interest (see Table 1), we are left with 1,591 observations available for the analysis. Of the 1,591 respondents, 505 (31.74%) respondents agree that a course taken online provides an equal educational value compared to in-person classroom teaching, while the remaining 1,086 respondents (68.26%) do not agree and thus believe that online courses have lesser educational value. A description of the covariates and the response variable, along with the main characteristic of the data is presented in Table 1.

Table 1

Descriptive Summary of the Variables

VARIABLE	DESCRIPTION	MEAN	STD
Age/100	Age (in years) divided by 100	0.44	0.18
Income/100,000	Mid-point of income category (in US dollars) divided by 100,000	0.63	0.48
		COUNT	%
Online Course	Indicates that the respondent has previously taken an online course for academic credit	352	22.12
(Age< 65)*Enroll	Indicates that the respondent is of age below 65 and currently enrolled in school	291	18.29
Female	Indicator variable for female gender	815	51.23
Post-Bachelors	Respondent's highest qualification is Masters, Professional or Doctorate	221	13.89
Bachelors	Respondent's highest qualification is Bachelors	356	22.38
Below Bachelors	Respondent holds a 2-year associate degree, went to some college with no degree, or attended technical, trade or vocational school after high school	482	30.30
HS and below	Respondent is a high school (HS) graduate or below	532	33.44
Full-time	Indicator for full-time employment	757	47.58
Part-time	Indicator for part-time employment	240	15.08
Unemployed	Indicator for either unemployed, student or retired	594	37.34
White	Indicator for a White respondent	1131	71.09
African-American	Indicator for an African-American respondent	257	16.15
Other Races	Indicator for a respondent who is either an Asian, Asian-American or belongs to some other race	203	12.76
Urban	Lives in an urban region	626	39.35
Suburban	Lives in a suburban region	760	47.77
Rural	Lives in a rural region	205	12.88
Northeast	Lives in the Northeast	220	13.83
West	Lives in the West	362	22.75
South	Lives in the South	724	45.51
Midwest	Lives in the Midwest	285	17.91
Opinion	Respondent answered 'Yes' to our question of interest	505	31.74
	Respondent answered 'No' to our question of interest	1086	68.26

In our sample, a typical individual is 44 years of age with a family income of 63 thousand US dollars. The survey recorded income as belonging to one of the following nine income categories: < 10k, 10k–20k, 20k–30k, 30k–40k, 40k–50k, 50k–75k, 75k–100k, 100k–150k and >150k, where k denotes a thousand dollars. We use the mid-point of each income category to represent the income variable, where $5,000 and $1,75,000 are used as the mid-point for the first and last income categories, respectively. With respect to online learning, we have a little more than one-fifth of the sample who have previously taken an online course for academic credit. A sizeable proportion of the sample, therefore, have had prior exposure to online learning. Individuals who are aged less than 65 and currently enrolled in school comprise a little less than one-fifth of the sample. Here, enrollment in school implies that the respondent is either attending high school, technical school, trade or vocational school, is a college undergraduate or in graduate school.

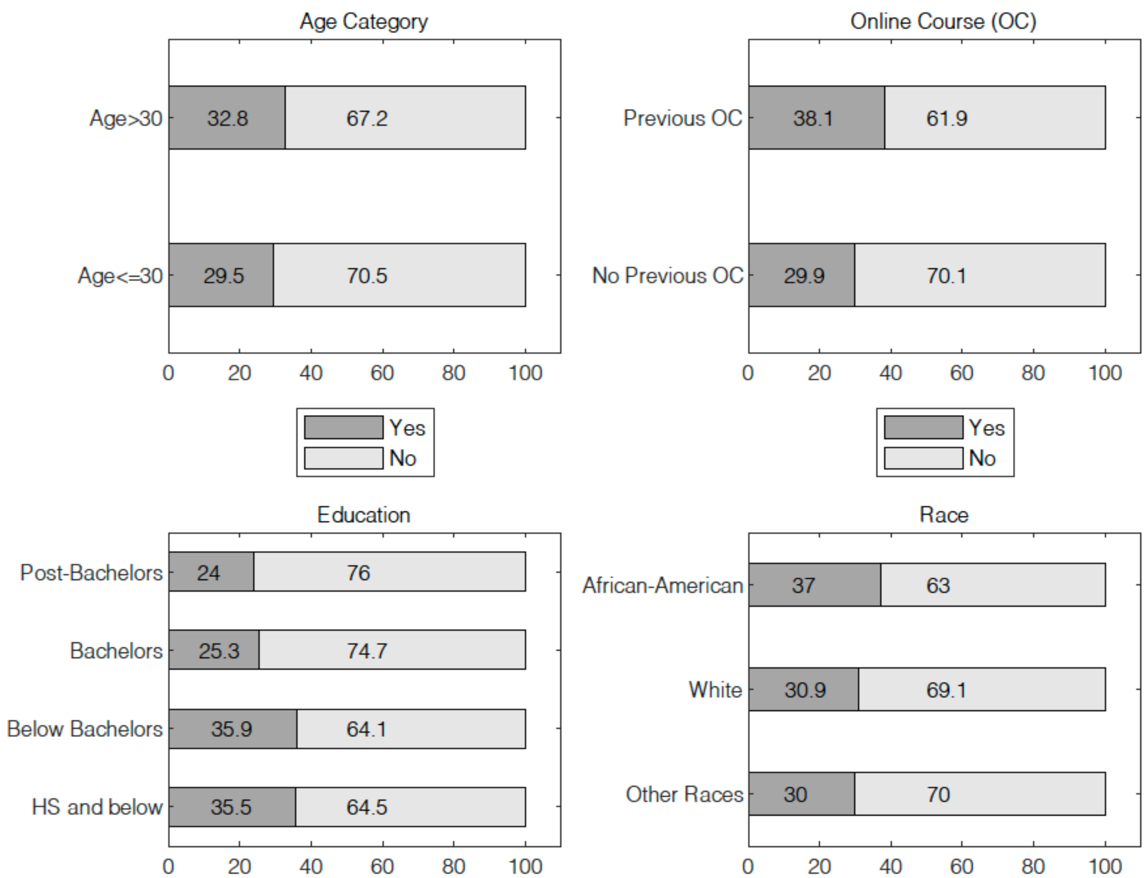
The sample has more females (51.23%) than males (48.77%), but both genders have approximately equal representation. Education has been classified into four categories with 'High School (HS) and below' forming the largest category (33.44%) followed by 'Below Bachelors' (30.30%). The smallest two educational categories are 'Bachelors' (22.38%) and 'Post-Bachelors' (13.89%). So, approximately two-thirds of the sample have less than bachelors education. With respect to employment status, about a little less than two-thirds (i.e., 62.66%) are either employed full-time or part-time, while the remaining percentage are either unemployed, students or retired individuals. Racial classification shows that more than two-thirds are White (71.09%), followed by African-Americans (16.15%) and all other races (12.76%). In terms of rural-urban classification, most of the sampled individuals live in the suburban areas (47.77%), followed by the urban areas (39.35%). The lowest proportion lives in the rural areas (12.88%). Regional classification as defined by the US Census Bureau shows that the largest percentage of the sample lives in the South (47.77%). This is followed by the West (22.75%), Midwest (17.91%), and Northeast (13.83%) regions.

Before we formally delve into modelling the dependent variable (i.e., public opinion on educational value of online learning relative to in-person classroom teaching), we explore its relationship with some selected independent variables or covariates (see Parker et al. (2011) for a report on data summary). To explore this association, we present a stacked bar graph in *Figure 1* with four panels, each portraying the relationship between the dependent variable and a single covariate. Each bar within a panel corresponds to a category of the covariate and displays the percentage of observations that says 'Yes' and 'No' to our question of interest. For example, the upper (lower) bar in Panel 1 shows that for people aged greater than (less than equal to) 30, 32.8% (29.5%) of the sample agree that online courses have the same educational value as in-person classroom teaching, while the remaining 67.2% (70.5%) do not agree. The other three panels of Figure 1 can be interpreted analogously.

We see from the first panel of *Figure 1* that the percentage of sample who says 'Yes' (and thus 'No') is approximately equal amongst the younger (Age<=30) and older (Age >30) population. From Panel 2 we note that, amongst the sample who have taken an online course for academic credit, a higher percentage (38.1%) says 'Yes' compared to those (at 29.9%) who have no previous online learning experience. Panel 3 suggests that the highly educated group (Bachelors and Post-Bachelors) are less likely to agree (1 in every 4 individual) about the equal educational value of online learning and classroom teaching, as compared to the lower educated group (where 1 in every 3 agrees). Similarly, the racial classification of response shows that the African-Americans are more likely to agree (37%) as compared to White (30.9%) and Other Races (30%).

Figure 1

Stacked bar graph displaying the percentage of observations corresponding to the two categories of public opinion (Yes and No) for each category of some selected covariates



The discussion involving the stacked bar graph only presents an association between the public opinion on the educational value of online learning relative to in-person classroom teaching and one covariate at a time, namely, age, previous participation in online course, education, and race. Such an association can be captured by regressing the dependent variable on a chosen covariate/regressor. However, inference based on such an analysis is unlikely to present the true relationship because there may be other determinants of the dependent variable which are correlated with the chosen covariate. If ignored, this may lead to estimation bias and incorrect inferences. For instance, let us suppose we are interested in the relationship between public opinion on online learning relative to in-person classroom teaching and the age category. To this end, we regress the dependent variable on age category. However, this relationship is likely to change when we control for previous participation in online course owing to the correlation between previous participation in online course and age. To net out such effects and understand the actual impact of a covariate on the dependent variable, we next turn to some formal econometric modelling.

Methodology

Quantile regression, as introduced by Koenker & Bassett (1978), looks at quantiles of the (continuous) response variable conditional on the covariates and thus provides, amongst other things, a comprehensive picture (as compared to traditional mean regression) of the effect of covariates on the response variable. Estimation involves minimizing the quantile loss function using linear programming techniques (Koenker, 2005). Interestingly, the quantile loss function appears in the exponent of the asymmetric Laplace (AL) distribution (Yu & Zhang, 2005), which makes minimization of the quantile loss function equivalent to maximization of the AL likelihood. This characteristic allowed Yu & Moyeed (2001) to construct a working likelihood and propose Bayesian quantile regression. However, when outcomes are discrete (e.g., binary, ordinal) estimation becomes challenging because quantiles for discrete outcomes are not readily defined. With discrete outcomes, the concern is to model the latent utility differential (say, between making a choice versus not making it or occurrence of an event versus its non-occurrence) facilitated through the introduction of a latent variable (Albert & Chib, 1993; Greenberg, 2012; Rahman, 2016). This applies to both mean and quantile regressions and is useful for estimation and inference.

Kordas (2006) introduced quantile regression for binary outcomes (or binary quantile regression[2]) and Benoit & Poel (2012) presented the Bayesian framework. The binary quantile model can be conveniently expressed using the latent variable z_i as follows,

$$z_i = x_i'\beta_p + \epsilon_i, \qquad \forall i = 1, \dots, n \qquad \textit{Equation 1}$$

$$y_i = \begin{cases} 1 & if \quad z_i > 0 \\ 0 & otherwise. \end{cases}$$

where x_i is a $k \times 1$ vector of covariates, β_p is a $k \times 1$ vector of unknown parameters at the p-th quantile (henceforth, the subscript p is dropped for notational convenience), ϵ_i follows an AL distribution i.e., $\epsilon_i \sim AL(0,1,p)$, and n denotes the number of observations. In our study, the latent variable z_i can be interpreted as the latent utility differential between online learning relative to in-person classroom learning. Whenever the observed response $y_i = 1$ (i.e., the respondent answers 'Yes' to our question of interest), propensity to online learning is likely to be high and z_i takes a value in the positive part of the real line. Similarly, when $y_i = 0$ (i.e., the respondent answers 'No' to our question of interest), the propensity to online learning is low and z_i takes a value in the negative part of the real line.

Algorithm 1 (MCMC Algorithm for Binary Quantile Regression)

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1. Sample $\beta | z, \omega \sim N(\tilde{\beta}, \tilde{B})$, where,

$$\tilde{B}^{-1} = \left(\sum_{i=1}^{n} \frac{x_i x_i'}{\tau^2 \omega_i} + B_0^{-1}\right) \text{ and } \tilde{\beta} = \tilde{B}\left(\sum_{i=1}^{n} \frac{x_i(z_i - \theta\omega_i)}{\tau^2 \omega_i} + B_0^{-1}\beta_0\right).$$

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[2] Binary quantile regression is a special case of ordinal quantile regression considered in Rahman (2016) and can be linked to the random utility theory in economics (Jeliazkov & Rahman, 2012; Train, 2009). For other developments on Bayesian quantile regression with discrete outcomes, please see Alhamzawi & Ali (2018), Alhamzawi & Ali (2020), Ghasemzadeh et al. (2020), Ghasemzadeh et al. (2018), Rahman & Vossmeyer (2019), Rahman & Karnawat (2019), and Bresson et al. (2021).

2. Sample $\omega_i | \beta, z_i \sim GIG\left(0.5, \tilde{\lambda}_i, \tilde{\eta}\right)$, for $i = 1, \dots, n$, where,

   $\tilde{\lambda}_i = \left(\frac{z_i - x_i'\beta)}{\tau}\right)^2$ and $\tilde{\eta} = \left(\frac{\theta^2}{\tau^2} + 2\right)$.

3. Sample the latent variable $z | y, \beta, \omega$ for all values of $i = 1, \dots, n$ from a univariate truncated normal (TN) distribution as follows,

$$z_i | y, \beta, \omega \sim \begin{cases} TN_{(-\infty, 0]}(x_i'\beta + \theta\omega_i, \tau^2\omega_i) & if \quad y_i = 0, \\ TN_{(0,\infty)}(x_i'\beta + \theta\omega_i, \tau^2\omega_i) & if \quad y_i = 1. \end{cases}$$

We can form a working likelihood from Equation 1 and directly use it to construct the posterior distribution, but this is not convenient for MCMC sampling. A preferred alternative is to employ the normal-exponential mixture of the AL distribution (Kozumi & Kobayashi, 2011). In this formulation, $\epsilon_i = \theta\omega_i + \tau\sqrt{\omega_i}\, u_i$, and the binary quantile model is re-expressed as,

$$z_i = x_i'\beta + \theta\omega_i + \tau\sqrt{\omega_i}\, u_i, \qquad \forall i = 1, \dots, n$$
$$y_i = \begin{cases} 1 & if \quad z_i > 0 \\ 0 & otherwise. \end{cases}$$

Equation 2

where $\theta = \frac{(1-2p)}{p(1-p)}$ and $\tau = \sqrt{\frac{2}{p(1-p)}}$ are constants, and $w_i \sim \mathcal{E}(1)$ is independently distributed of $u_i \sim N(0,1)$. Here, the notations $\mathcal{E}$ and N denote exponential and normal distributions, respectively. It is clear from formulation Equation 2 that the latent variable $z_i | \beta, \omega_i \sim N(x'_i\beta + \theta\,\omega_i, \tau^2\omega_i)$, thus allowing access to the properties of normal distribution.

By the Bayes' theorem, the complete data likelihood from Equation 2 is combined with a normal prior distribution on β (i.e., $\beta \sim N(\beta_0, B_0)$) to form the complete data posterior. This yields the following expression,

$$\pi(z, \beta, \omega | y) \propto \{\textstyle\prod_{i=1}^{n}[I(z_i > 0)I(y_i = 1) + I(z_i \leq 0)\, I(y_i = 0)]N(z_i | x'_i\beta + \theta\omega_i,\ \tau^2\omega_i) \times \mathcal{E}(\omega_i | 1)\}\, N(\beta_0, B_0).$$

Equation 3

The full conditional posterior densities for (z, β, ω) can be derived from Equation 3 and the model can be estimated using the Gibbs sampler (Geman & Geman, 1984)—a well-known MCMC technique—presented in Algorithm 1. The sampling algorithm is straightforward and involves sampling β conditional on (z, ω) from an updated normal distribution. The latent weight ω conditional on (β, z) is sampled from a Generalized Inverse Gaussian (GIG) distribution (Devroye, 2014). Finally, the latent variable z conditional on (y, β, ω) is sampled from a truncated normal distribution (Robert, 1995).

Results and Discussion

Table 2 presents the posterior means, and standard deviations of the parameters from the Bayesian estimation of probit model (Albert & Chib, 1993), and the binary quantile regression at the

10th, 25th, 50th, 75th and 90th quantiles. We assume the following diffuse prior distribution: $\beta \sim N(0_k, 1000 * I_k)$, where N and I denote a multivariate normal distribution and an identity matrix of dimension k, respectively. The results are based on 20,000 MCMC iterations after a burn-in of 5,000 iterations. The inefficiency factors were calculated using the batch-means method (Chib, 2013; Greenberg, 2012). For the five chosen quantiles, they lie in the range (6.34, 10.94), (4.18, 5.39), (2.53, 3.16), (2.38, 2.58), and (3.35, 4.24). The numbers are small which indicates a low cost of working with MCMC draws. Trace plots, not shown, reveal good mixing of the chains. With respect to model comparison measures, we calculate the conditional log-likelihood, Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) at the posterior mean. The corresponding numbers for the probit model are (-959.43, 1956.86, 2058.93), and those for the five quantiles are (-960.24, 1958.47, 2060.54), (-960.18, 1958.36, 2060.43), (-960.00, 1958.00, 2060.07), (-959.90, 1957.80, 2059.87), and (-959.16, 1956.33, 2058.40). We also compute the covariate effects for the statistically significant variables in the probit model and for each of the five quantiles. These are presented in Table 3[3] and are calculated marginally of the remaining covariates and the parameters (Bresson et al., 2021; Chib & Jeliazkov, 2006; Jeliazkov et al., 2008; Jeliazkov & Rahman, 2012; Jeliazkov & Vossmeyer, 2018; Rahman & Vossmeyer, 2019).

While many of the results are in line with extant literature, our results provide some useful insights into the differences across quantiles. As previously noted, we are modelling the latent utility differential between online and in-person classes. Therefore, the results may be interpreted as a utility index of online education. Large positive (negative) values of this index signify high (low) propensity to favor online classes, and values around zero would indicate relative indifference between the two alternatives. A bird's-eye view of the results shows that age, past online experience, full time employment and gender have a positive effect on the propensity to favor online education. Higher level of educational degree, on the other hand, has a negative effect on the willingness towards online education. We also note some amount of regional variation in the propensity to favor online classes. In what follows, we focus on each variable separately to better understand the results.

The coefficient for age is positive and statistically different from zero at 95% probability level[4] across all quantiles. This is not surprising as online courses invariably attract an older demographic (Crain & Ragan, 2017). Goodman et al. (2019) find similar results highlighting that on average, the online applicants were 34 years of age compared to 24 years for in–person applicants in their study. Besides, our result is perhaps indicative of mid-career professionals favoring online classes since several online courses cater to those active in the workforce, requiring professional development or retaining by employers (Kizilcec et al., 2019). From the calculated covariate effects in Table 3, we see that the covariate effect of age is between 1.7 to 2.2 percentage points across the quantiles. Stronger effects are visible in the upper part of the latent index.

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[3] The covariate effects for previous online course, full-time employment, post-bachelors, bachelors, Northeast and South are calculated on the respective sub-samples and are a discrete change compared to their base groups respectively. The covariate effect for female is calculated on the full sample and is a discrete change compared to male.

[4] This means that the 95% probability interval i.e., posterior mean ± 1.96 * posterior standard deviation, does not contain zero. The default probability level is 95% and references to it is dropped henceforth.

Table 2
Posterior mean (Mean) and standard deviation (STD) of the parameters from the Bayesian estimation of probit regression and binary quantile regression.

	PROBIT		QUANTILE 10TH		25TH		50TH		75TH		90TH	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Intercept	−0.80	0.20	−14.02	2.17	−5.03	0.85	−1.69	0.45	−0.23	0.46	1.58	0.97
Age/100	0.58	0.23	5.39	2.44	2.24	0.92	1.17	0.49	1.34	0.52	3.35	1.14
Income/100,000	0.37	0.26	4.20	2.73	1.70	1.13	0.92	0.58	0.87	0.59	1.02	1.23
Sq-Income	−0.28	0.14	−3.18	1.57	−1.30	0.65	−0.69	0.33	−0.63	0.32	−0.86	0.64
Online Course	0.31	0.09	2.80	0.83	1.14	0.35	0.64	0.19	0.75	0.21	1.74	0.48
(Age< 65)*Enroll	0.02	0.11	0.25	1.13	0.12	0.43	0.07	0.22	0.00	0.24	0.00	0.51
Female	0.14	0.07	1.72	0.71	0.71	0.28	0.36	0.15	0.27	0.15	0.53	0.33
Post-Bachelors	−0.45	0.12	−4.76	1.32	−1.95	0.55	−1.02	0.28	−0.98	0.27	−2.09	0.54
Bachelors	−0.40	0.10	−4.19	1.21	−1.69	0.44	−0.90	0.23	−0.87	0.23	−1.81	0.48
Below Bachelors	−0.09	0.09	−1.03	0.83	−0.44	0.35	−0.26	0.19	−0.17	0.20	−0.27	0.47
Full-time	0.27	0.08	2.76	0.94	1.13	0.37	0.58	0.19	0.58	0.19	1.28	0.42
Part-time	0.17	0.11	1.67	1.15	0.68	0.49	0.35	0.24	0.41	0.24	0.93	0.51
White	−0.01	0.11	0.08	1.12	0.06	0.48	0.03	0.24	−0.05	0.24	−0.18	0.49
African-American	0.21	0.13	2.05	1.26	0.93	0.55	0.48	0.28	0.43	0.31	0.87	0.66
Urban	−0.10	0.11	−1.00	1.12	−0.36	0.47	−0.23	0.24	−0.25	0.25	−0.35	0.55
Suburban	0.06	0.11	0.58	1.04	0.32	0.44	0.11	0.23	0.12	0.24	0.43	0.56
Northeast	−0.29	0.12	−3.09	1.31	−1.23	0.56	−0.63	0.28	−0.63	0.28	−1.53	0.59
West	−0.06	0.11	−0.44	1.04	−0.18	0.42	−0.10	0.22	−0.18	0.25	−0.58	0.56
South	−0.22	0.09	−2.34	0.96	−0.93	0.39	−0.48	0.20	−0.46	0.22	−1.14	0.51

Next, we note that individuals with a full-time employment status favor educational value of online classes positively in comparison to base category (unemployed, students or retired individuals). The coefficient for full-time employment, compared to the base category, is statistically positive across the quantiles.[5] The coefficients for part-time employment are positive but the effects are not statistically different from zero, implying that regardless of the latent utility for online education, part-time employment does not impact the decision.[6] In fact, from Table 3, the covariate effect of full-time employment increases the willingness for online class by 7.8 percentage points in the 10th quantile and consistently increases across quantiles to about 8.7 percentage points in the 90th quantile. For individuals who are in the lower part of the latent index, employment impacts their valuation for online education less than those in the upper quantile.

Turning to previous exposure to digital learning, we find that individual's propensity of valuing online education is higher for those who have had past participation in online classes for academic credit than those who have not. We find positive effects of previous exposure to online education across the quantiles of the utility scale, similar to Astani et al. (2010), Williams (2006), and Goode (2010). A positive stance towards online education is therefore undeniably linked to previous exposure and use of technology. The covariate effect of previous online class ranges between 9.5 to 11.1 percentage points across the quantiles (see Table 3). Although the effect somewhat plateaus at the 75th quantile, our findings suggest that past online experience increases the probability of valuing online classes most for those with higher utility for online education.

We also find that females are more in favor of online education relative to males. This finding is in consonance with Fortson et al. (2007), who propose that female college students are more likely to go online for communicative and educational purposes while male college students are more likely to use the internet as a source of entertainment. Perhaps the noted gender differential could also be a result of differences in past usage of internet.[7] Furthermore, online education allows for flexible schedules that individuals can customise around their family and job constraints more easily (Goodman et al., 2019). This greater flexibility in schedule likely implies greater willingness for online education for females. The covariate effect of females, displayed in Table 3, shows that being female increases the probability of valuing online education by 5.3 to 3.5 percentage points from 10th to 90th quantiles respectively. We find the strongest effect of female in the 25th quantile and it reduces at the 90th quantile. At higher utility, females are more similar to males than at lower utility.

Next, we find that the coefficients for different levels of education are consistently negative, relative to the base category (HS and below), across the quantiles. In each quantile, the post-bachelor's category shows a large negative propensity for online classes vis-à-vis traditional learning. The effects are also negative for those with a bachelor's degree compared to those with HS education or below. While the effects are negative for below-bachelor's degree, they are not statistically different in comparison to the base category. This is useful in understanding the differences in preferences between individuals with different educational qualifications. Highly

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[5] Our result for full-time employment is in agreement with the evidence that demand for online education is high for employed mid-career professionals, or those who seek professional development (Kizilcec et al., 2019; Simmons, 2014). It appears to be commonplace for employers to sponsor their employees' enrollment into online courses for training purposes as observed by Goodman et al. (2019) and Deming et al. (2015).

[6] The National Post-Secondary Student Aid Study (NPSAS) for 2011–12 that includes a nationally representative cross-section of institutions and students shows that online students are older and more likely to be working full-time while enrolled (Deming et al., 2015).

[7] The proportion of individuals with previous experiences of online education is higher for females in our sample, with 55% of females having taken an online course for credit before.

educated respondents report diminished value of online classes in comparison to those with a HS degree or below. This points to some degree of stigma towards online education as the level of educational qualification rises (Kizilcec et al., 2019). Greater intensity of learning and teaching at graduate or post graduate levels likely decreases the utility from online classes. Students perceive better learning from face-to-face interactions, and visualizing materials. The self-regulatory nature of physical classroom teaching perhaps enables students to track their understanding of the course in a more satisfactory manner. Our result finds support in Krieg & Henson (2016); Hart et al. (2018); Chen et al. (2013); Anstine & Skidmore (2005); and Fendler et al. (2011), where they document lower performance and greater likelihood of repeating the same course, for university and college students taking online classes relative to those taking them in traditional classroom formats. On similar lines Otter et al. (2013) note that students believe that they must do the teaching and learning on their own in online courses in contrast to what they feel about the time and effort from faculty for traditional courses. This perhaps reduces the value they attach to online education at higher degree levels. According to O'Neill & Sai (2014), traditional classes also allow for better relationship and lines of communication with the instructor. Other studies suggest that students face difficulty in keeping up motivation in online classes. This is likely to become more prominent at higher levels of education.[8] Examining our covariate effects from Table 3, we see that the effects are negative and vary between 13.9 to 15.1 percentage points for individuals with a post-bachelor's degree. The result from the 50th quantile is similar to the probit result implying a 15.1 percentage points reduction in the probability of valuing online education. The covariate effects are slightly lower for those with a bachelor's degree and range between 12.1 to 13.7 percentage point decline in their opinion about online classes.

Looking at geographical locations, we note some significant regional effects in driving the opinion about online education. We find negative effects for those living in the Northeast, the South, and the West relative to the Midwest (the omitted category). However, the effects are not statistically important for those residing in the West. We see the largest negative effects in the Northeast across all quantiles, followed by the South, in comparison to the Midwest.[9] Use of technology, student population, course design and support provided by the universities, as well as the philosophies of universities in the region are likely drivers of the regional differences in the popularity of online courses. Regions where online education is more popular demonstrate higher educational value of online courses.[10] Xu & Jaggars (2013) highlight the importance of the institutional state in determining the cultural capital around technology. Allen & Seaman (2007) also suggest that the Southern states represented over one-third of total online enrollments in 2005–06 and the proportion of Southern institutions with fully online programs is steadily rising.[11] Our covariate effect calculations indicate that in the Northeast, the probability of favoring online classes

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[8] Individual's prior experience with online courses and their performance likely play a role in determining the value they attach to online education. As per Parker et al. (2011) roughly 39% of those who have taken an online course before respond favorably to online educational value whereas about 27% of those with no prior online education favorably value online classes.

[9] Use of technology in the Mid-west and the South is higher compared to the East. In fact, the East coasters are found to lag behind the rest of the country in some aspects of technology adoption as per Parker et al. (2011).

[10] Miller (2014) states that universities in Arizona are considered to be early adopters of online teaching techniques, in fact preferring faculty with experience in technology.

[11] Regions with students having high levels of technological proficiency are more likely to take courses which integrate technology, major in technology-rich disciplines, and pursue technology-rich careers (Xu & Jaggars, 2013).

reduces by 9.1 to 10.2 percentage points relative to the Midwest, across the quantiles. We find the highest negative effect for those in the 90th quantile. In the Southern regions compared to the Midwest, the propensity to value online education reduces by 6.9 to 8 percentage points.

We also examine the effect of race and find no noteworthy racial differences in the willingness towards online education relative to in-person education. Specifically, the coefficients for White, relative to the base category (Other Races), are statistically equivalent to zero. Similarly, the coefficients for African-Americans across the quantiles are statistically equivalent to zero. This likely indicates that, after controlling for different educational levels and previous exposure to online learning, individuals

Table 3

Covariate Effect

		QUANTILE				
	PROBIT	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Age	0.0200	0.0175	0.0181	0.0185	0.0202	0.0219
Online Course	0.1088	0.0952	0.0971	0.1048	0.1114	0.1104
Female	0.0486	0.0535	0.0550	0.0549	0.0415	0.0351
Post-Bachelors	−0.1512	−0.1447	−0.1479	−0.1511	−0.1478	−0.1395
Bachelors	−0.1356	−0.1306	−0.1317	−0.1379	−0.1332	−0.1211
Full-time	0.0857	0.0784	0.0804	0.0813	0.0853	0.0874
Northeast	−0.0954	−0.0920	−0.0914	−0.0918	−0.0940	−0.1024
South	−0.0777	−0.0806	−0.0797	−0.0807	−0.0693	−0.0723

across racial groups seem to hold similar attitudes about the online classes as an educational tool. Our results fall in line with Cotten & Jelenewicz (2006), Odell et al. (2000), Jones et al. (2009), and Bowen et al. (2014), who note that the digital divide upheld by race may be narrowing, and in some cases negligible among college campuses in the US. Contrary to this, Figlio et al. (2013) and Mann (2019), find more racial disparity in the outcome and outreach of online education.

The coefficients for urban areas are negative and for the suburban areas are positive compared to the base group of rural residents. However, the effects are not statistically important implying that area of residence does not seem to impact the opinion about online classes. Interestingly, income levels have a positive effect across the quantiles but once again the effects are not statistically different from zero. Although, Horrigan & Rainie (2006) and Rauh (2011) find that affluent families have better access to internet, we find no convincing evidence that income plays a role in determining opinion about online classes vis-à-vis traditional classes.

Conclusion

Technological advancements and the rising cost of higher education have rendered online education as an attractive substitute or a complementary technique for teaching and learning. With the online enrollment growth rate in the US at 9.3%, over 6.7 million students were estimated to have taken at least one online course in 2012 (Allen & Seaman, 2013). Considering this trend, in this paper, we examine *public opinion* about the value of online learning methods in comparison to in-person education across the US. Public opinion often influences policy making in the US as documented, amongst others, in Shapiro (2011) and Burstein (2003). Therefore, results from a study of public opinion on the mode of teaching-learning may be useful to researchers as well as policymakers.

Our approach provides a rich view of how the demographic covariates influence public opinion about the educational value of online classes, thereby, better informing future educational policies. While there seems to be some degree of adaptation to specific online courses offered by traditional universities as blended learning, reservations about the quality and rigour of fully online degree programs remain. Related to this, we find that willingness towards online versus in-person classes is lower for highly educated individuals, possibly due to limited intellectual stimulation and growth that may eventually hinder their labour market outcomes. This indicates that students at the graduate and post-graduate levels continue to derive greater value from in-person interactions. Thus, universities should perhaps recognize that fully online degree programs are less likely to be successful for such students. Our results also point to important effects of age, employment status, and gender on the propensity towards online education across the latent utility scale. From a policy standpoint, this speaks to the importance of designing tailored online courses for population groups with greater requirements of flexibility in their schedules owing to personal and professional constraints. In addition, we find no evidence of effects of race and income on the propensity for online education. This is indicative of online classes democratizing access to education. However, it may be interesting to examine the trade-off between a perceived decrease in academic outcomes and efficacy of online education versus the increase in the exposure of education to previously inaccessible population from a policy perspective.

Following these policy implications, we conclude with three main questions for future work. First, creating an in-depth, systematic support for both faculty and students, in transitioning from traditional to online teaching-learning platforms, is not an inexpensive venture. With considerable fixed costs incurred in training, course creations and delivery methods for online education (Ginn & Hammond, 2012; Xu & Jaggars, 2013), what would be the incentives to switch back to in-person classrooms or blended formats in a post-pandemic general equilibrium? Second, that upward mobility in teaching colleges are largely influenced by student feedback and evaluations is well established (Y. Chen & Hoshower, 2003; Krautmann & Sander, 1999; McClain et al., 2018). If we consider the current health landscape across the globe as a period of deviation from the true nature of dynamics between education and technology, one ought to think about how student feedback during this phase will contribute to upward mobility of faculty. Third, with evidence that online delivery improves access to education in the US (Goodman et al., 2019), it may be worthwhile to explore public opinion on the value of online education vis-à-vis traditional education in the developing world, parts of which invariably suffer from poor digital access and connectivity.

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About the Authors

Manini Ojha
Jindal School of Government and Public Policy, O. P. Jindal Global University, Sonipat, India
mojha@jgu.edu.in
https://orcid.org/0000-0001-8933-6560
Manini Ojha is an Assistant Professor at the Jindal School of Government and Public Policy, O. P. Jindal Global University. She did her Ph.D. in Economics (2018) from Southern Methodist University, Dallas, USA. Her areas of research are Applied Microeconometrics, Empirical Development Economics, Economics of Education, Economics of the Households, Economics of Gender and Labour Economics. She has taught courses in Microeconomics, Macroeconomics, Public Economics, Econometrics, and Statistics in the United States, and India.

Mohammad Arshad Rahman
College of Business, Zayed University, Abu Dhabi, UAE, and Department of Economic Sciences, Indian Institute of Technology, Kanpur, India
marshad@iitk.ac.in
https://orcid.org/0000-0001-8434-0042
Mohammad Arshad Rahman is an Associate Professor of Finance in the College of Business at Zayed University (Abu Dhabi Campus) and a tenured Associate Professor in the Department of Economic Sciences at the Indian Institute of Technology, Kanpur, India. He did his Ph.D. in Economics (2013) from the University of California, Irvine, USA, and has research interest in Bayesian Econometrics, Quantile Regression, Markov chain Monte Carlo Techniques, and Applied Econometrics. Professor Rahman has taught courses in Economics, Econometrics, Statistics, and Finance in the United States, India, and the United Arab Emirates.

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